



# Trust Aware Aquila Optimizer based Secure Data Transmission for Information Management in Wireless Sensor Networks

Abedallah Zaid Abualkishik<sup>1</sup>, Ali A. Alwan<sup>2</sup>

<sup>1</sup> American University in the Emirates, Dubai, United Arab Emirates

<sup>2</sup> School of Theoretical & Applied Science, Ramapo College of New Jersey, USA

Emails: abedallah.abualkishik@aue.ae; aaljuboo@ramapo.edu

## Abstract

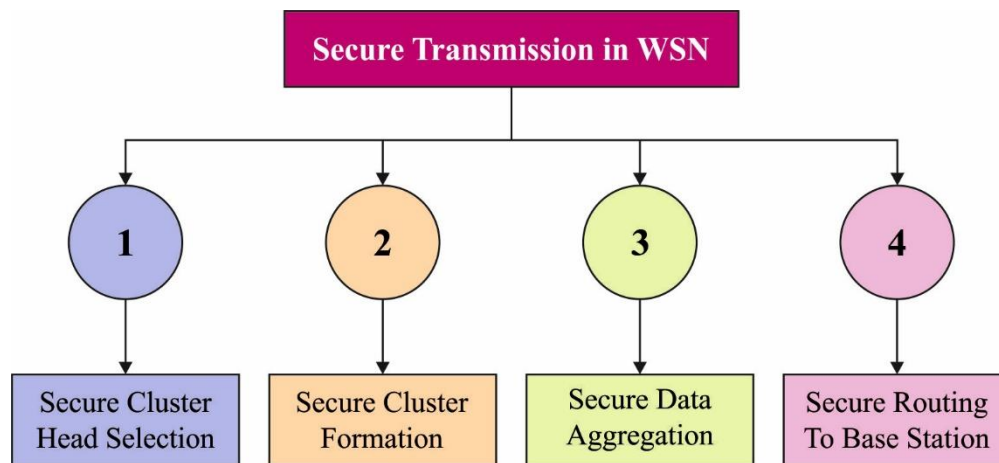
The province of wireless sensor network (WSN) is increasing continuously because of wide-ranging applications, namely, monitoring environmental conditions, military, and many other fields. But trust management in the WSN is the main objective as trust was utilized once cooperation among nodes becomes crucial to attaining reliable transmission. Thus, a new trust-based routing protocol is introduced to initiate secure routing. This study focuses on the design of Trust Aware Aquila Optimizer based Secure Data Transmission for Information Management (TAAO-SDTIM) in WSN. The presented TAAO-SDTIM model mainly intends to achieve maximum security and information management in WSN. The presented TAAO-SDTIM model determines optimum set of routes to base station (BS) utilizing a fitness function involving three parameters like residual energy (RE), distance to BS (DBS), and trust level (TL). The incorporation of the trust level of the nodes in the route selection process aids in appropriately selecting highly secure nodes in the data transmission procedure. For ensuring the enhanced performance of the TAAO-SDTIM model, a wide range of experiments are executed and the results pointed out the improved outcomes of the TAAO-SDTIM model over the other recent approaches.

**Keywords:** Trust, Security, Information management, Wireless sensor networks, Fitness function.

## 1. Introduction

Progresses in sensor technologies enable wireless sensor networks (WSNs) in numerous modern regions including vehicle traffic checking, smart industries, IoT, public security organizations, and so on [1]. WSNs are applied in many fields, for example, in medical care, ecological detecting, modern checking, and vehicle to vehicle correspondence [2]. A WSN has included a base station (BS) and a few circulated sensor nodes (SN) which, through the detecting of specific actual boundaries, speak with the climate. The BS is entrusted with getting, handling, and giving information to the end-client for decision making [3]. Nodes in WSN depend on their ready, restricted, non-battery-powered, and non-inconsistent batteries. Also, SNs are restricted away, memory, and CPU handling abilities [4]. For the most part, the SNs use energy while apportioning, getting, or sending the data as these nodes adjust non-battery-powered battery, which goes on for a very long time or years. Consequently, energy proficiency is a significant objective in WSN as it is responsible for further developing the organization lifetime, which is satisfied by choosing the appropriate nodes as CHs to lay out got routing [5]. Along these lines, bunching is a significant worldview for laying out secure correspondence among SNs. The bunching offers ideal answers for starting tied down correspondence because of its inherent characteristics for saving energies and its suitability for managing huge estimated networks. Nonetheless, the regular group based convention thinks about every SN as trustworthy, which might prompt choice of unsure nodes as CH. Adjusting

dubious nodes as CHs may influence the ease of use and the security of the fundamental organization [6]. Fig. 1 depicts the secure transmission in WSN.

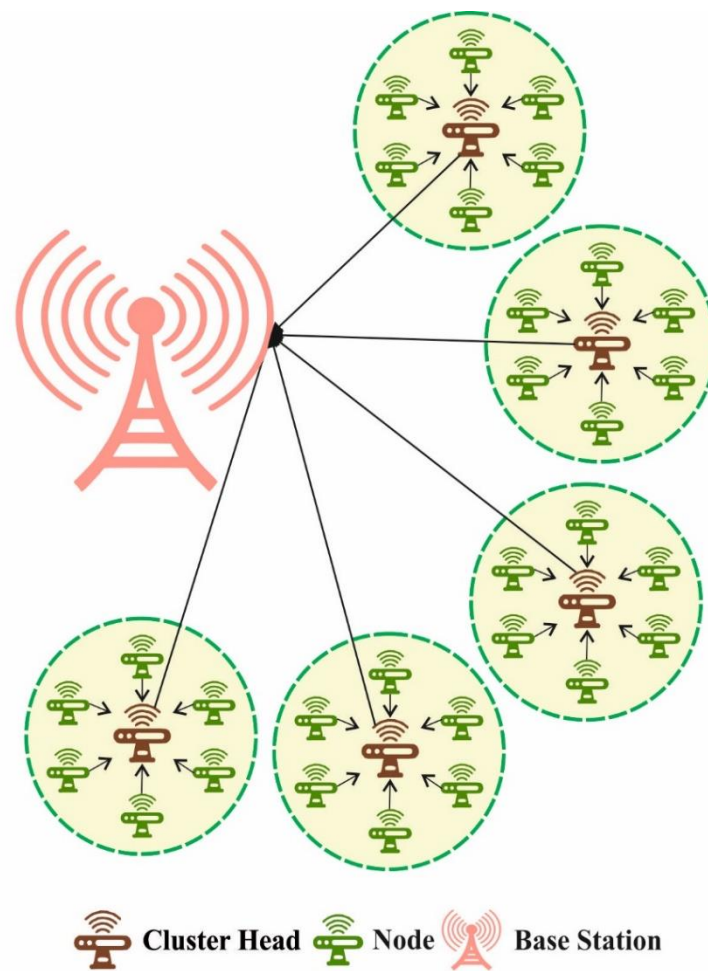


**Fig. 1. Secure transmission in WSN**

A few routing conventions are planned in the WSN for routing the information to other SNs with secure correspondence [7]. The routing in the WSN is separated into three routing procedures in light of the design of the organization. The places of the SNs are adjusted for routing information into the organization in routing in light of area, though in level based routing, all nodes are apportioned equivalent jobs in view of the usefulness, and in progressive based routing, and nodes will generally play different organization jobs [8]. The routing convention will in general be versatile assuming the framework boundaries are controlled for adjusting the current states of organization and reachable energy levels. Besides, the procedures in view of convention activity can be arranged into various methods, be specific rational based, multipath-based, exchange based, question based, and QoS based routing strategies. The proactive conventions figure the courses ahead of time before they are really required, while the responsive convention registers the courses on an on-request premise [9]. Customary routing conventions communicate the traffic alongside the foreordained ways, which starts intricacies with untrustworthy remote medium [10]. Fig. 2 demonstrates the process of cluster based WSN.

In [11], proposed two new heuristics procedures that are a clustered gravitational routing algorithm and gravitational approach-based clustering method for offering an optimum solution for effective routing and clustering. Shafiq et al. [12] proposed the Robust Cluster Based Routing Protocol (RCBRP) to recognize the routing path whereby lesser energy is expended to improve lifespan of the network. The researcher in [13] describes the fundamental of each abovementioned protocol and fundamental architecture of WSN and a homogeneous effective DEC based selection likelihood related multitier arbitrary possibility protocol or agriculture wireless sensor network is presented. In [14], a non-uniform clustering routing method based on efficient energy consumption (UCEEC) has been presented. The technique is integrated with the features of multiple path fading of farmland environmental signal. Rathore et al. [15] developed a state-of-the-art method to select CHs. The target of the CHs based on node energy and node distance. The CH selection aim is to minimize power usage and to improve the lifespan of the network by presenting the minimum shortest relay node.

This study focuses on the design of Trust Aware Aquila Optimizer based Secure Data Transmission for Information Management (TAAO-SDTIM) in WSN. The proposed TAAO-SDTIM model determines optimal set of routes to base station (BS) using a fitness function (FF) containing three parameters such as residual energy (RE), distance to BS (DBS), and trust level (TL). The incorporation of the trust level of the nodes in the route selection process aids in appropriately selecting highly secure nodes in the data transmission procedure. For ensuring the enhanced performance of the TAAO-SDTIM model, a wide range of experiments are implemented.



**Clustering Process using Aquila Optimizer: Residual Energy, Distance, Trust Level**

**Fig. 2. Process of Cluster based WSN**

**2. Design of Secure Data Transmission Approach**

In this study, a novel TAAO-SDTIM model is presented to achieve maximum security and information management in WSN. The proposed TAAO-SDTIM model determines optimal set of routes to BS using a FF comprising three parameters like RE, DBS, and TL.

**2.1 Overview of AO**

AO is proposed in the following. AO initiates by defining the first value for a set of  $N$  individuals  $X$  as follows:

$$X_{ij} = r_1 \times (UB_j - LB_j) + LB_j, i = 1,2, \dots, N, j = 1,2, \dots, Dim \quad (1)$$

Where,  $r_1$  represent an arbitrary number within[0,1].  $LB_j$  and  $UB_j$  denotes the lower and upper bounds at dimension  $j$ , correspondingly  $Dim$  indicates the dimensional of test problem [16]. Like other meta-heuristic methods, AO has exploration and exploitation phases, to upgrade the present individual. The exploration stage initiates if  $t \leq (\frac{2}{3}) * T$ , and it has two approaches; the initial one is shown in the following:

$$X_1(t+1) = X_{best}(t) \times \left(\frac{1-t}{T}\right) + (X_M(t) - X_{best}(t) * rand), \quad (2)$$

In which,  $T$  denotes the total amount of iterations.  $X(t)$  indicates the optimal individual attained at present iteration  $t$ , whereas the factor  $\left(\frac{1-t}{T}\right)$  is employed for managing the search at the time of exploration stage. Additionally, the  $X(t)$  denotes the individual average amongst the dimensions, as follows:

$$X_M(t) = \frac{1}{N} \sum_{i=1}^N X(t), \forall j = 1, 2, \dots, Dim \quad (3)$$

In the next exploration phase, the AO based on Levy flight distribution to upgrade the present individual as follows:

$$X_2(t+1) = X_{best}(t) \times Levy(D) + X_R(t) + (y - x) * rand, \quad (4)$$

Whereas  $X_R$  signifies an arbitrarily selected individual. Levy ( $D$ ) represent the Levy flight distribution determined by:

$$Levy(D) = s \times \frac{u \times \sigma}{|v|^\beta}, \sigma = \left( \frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right) \quad (5)$$

In Eq (5),  $s = 0.01$  and  $\beta = 1.5$  denotes constant values,  $u$  and  $v$  represent arbitrary values within  $[0,1]$ . In Eq. (4),  $y$  and  $x$  are utilized for stimulating the spiral shape as follows:

$$y = r \times \cos(\theta), x = r \times \sin(\theta) \quad (6)$$

$$r = r_1 + U \times D_1, \theta = -\omega \times D_1 + \theta_1, \theta_1 = \frac{3 \times \pi}{2} \quad (7)$$

Now  $r_1 \in [0,20]$  denotes random value.  $\omega = 0.005$  and  $U = 0.00565$  indicate small value.

There are 2 approaches are utilized for stimulating the exploitation capacity of individuals at the time of search method [17]. The initial technique based on the optimal solution ( $X_{best}$ ), and the average of individual position ( $X$ ):

$$X_3(t+1) = (X_{best}(t) - X_M(t)) \times \alpha - rand + ((UB - LB) \times rand + LB) \times \delta, \quad (8)$$

Where  $rand \in [0,1]$  signifies arbitrary value.  $\alpha$  and  $\delta$  denote the exploitation adjustment parameter.

The next exploitation technique based on  $X_{best}$ , Levy, and quality function  $QF$ .

$$X_4(t+1) = QF \times X_{best}(t) - (G_1 \times X(t) \times rand) - G_2 \times Levy(D) + rand \times G_1, \quad (9)$$

In which the major objective of utilizing  $QF$  is to balance the searching technique, and it can be determined by:

$$QF(t) = t^{\frac{2 \times rand() - 1}{(1-T)^2}} \quad (10)$$

$G_1$  characterizes distinct motions employed for tracking the optimal solution, and it can be determined by

$$G_1 = 2 \times rand() - 1 \quad (11)$$

Now,  $G_2$  is reduced from 2 to 0, and it can be expressed by

$$G_2 = 2 \times \left(1 - \frac{t}{T}\right) \quad (12)$$

In which  $rand$  denotes an arbitrary number.

## 2.2 Process involved in TAAO-SDTIM Model

In routing, the FF of routing method denotes the data transmission path in CH to sink node. The significance of FF is interrelated to CH has been accessible in the network, and furthermore, location is added from the sink. The dominance of FF is related to  $m + 1$ , whereas  $m$  denotes the amount of CH involved. Here,  $F_i = (F_{i,1}(t), F_{i,2}(t) \dots F_{i,m+1}(t))$  represent  $i^{th}$  FF, and the position  $F_{i,d}, \forall 1 \leq i \leq m + 1, \forall d 1 \leq d \leq m + 1$ , define following hop transmitted the information to BS. It is extremely attentive to defining optimal path from CH to sink. It is accomplished by using FF in different sub-objectives such as node energy, degree, and distance. For sending information, consecutive hop accomplishes the information and transfer it to BS. Consequently, maximal RE of following hop is prioritized obviously. Additionally, major sub-objective with energy  $f1$  is improved as follows by:

$$f1 = \sum_{i=1}^m E_{CHi} \quad (13)$$

Distance is denoted as distance among CH to next hop and sink. When the distance is minimal then the power usage rate has been minimized. The following objective to reduce the distance among CH to sink is evaluated as follows:

$$f2 = \frac{1}{\sum_{i=1}^m \text{dis}(\text{CH}_i, \text{NH}) + \text{dis}(\text{NH}, \text{BS})} \quad (14)$$

Trust factor (TF): initially, the comprehensive vehicle was described that TF is one. The value of TF was minimized by abnormal predictive method when the vehicle procedure the anomalous task and vehicle is named a malicious vehicle.

$$[1] \quad f_2 = \sum_{j=1}^m \frac{1}{m} (TF_j) \quad (15)$$

Subsequently, the weighted sum is implemented for sub-objective and converted to single objective. Here,  $\alpha_1, \alpha_2$  &  $\alpha_3$  indicates the weight allocated to each sub-objective, and  $\alpha_i \in (0,1)$  and  $\alpha_1 + \alpha_2 + \alpha_3 = 1$ .

$$\text{Fitness} = \alpha_1(f1) + \alpha_2(f2) + \alpha_3(f3) \quad (16)$$

### 3. Experimental Analysis

This section inspects the experimentation outcomes of the TAAO-SDTIM model with existing models.

**Table 1 PDR analysis of TAAO-SDTIM method with exiting methods on Blackhole Attack (50 Nodes)**

Packet Delivery Ratio (%)				
No. of Rounds	TAAO-SDTIM	CHICD	FABC	ABC
0	100.00	100.00	100.00	100.00
10	95.80	87.01	79.09	72.94
20	86.13	78.21	72.06	65.02
30	81.91	73.46	69.07	62.38
40	79.09	69.24	65.02	58.51
50	74.52	66.43	61.86	55.17
60	70.12	63.79	59.22	49.55
70	66.78	60.27	56.58	47.44
80	63.79	58.16	52.54	43.04
90	62.21	56.40	51.66	41.10
100	60.63	56.05	50.07	38.99

Table 1 and Fig. 3 examines the PDR of the TAAO-SDTIM model with other models under blackhole attacks with 50 nodes [18]. The experimental values indicated that the TAAO-SDTIM model has resulted in maximum PDR over the other techniques. For instance, with 10 rounds, the TAAO-SDTIM model has offered higher PDR of 95.80% whereas the CHICD, FABC, and ABC models have obtained lower PDR of 87.01%, 79.09%, and 72.94% respectively. Along with that, with 50 rounds, the TAAO-SDTIM system has obtainable greater PDR of 74.52% whereas the CHICD, FABC, and ABC techniques have obtained minimum PDR of 66.43%, 61.86%, and 55.17% correspondingly. Meanwhile, with 100 rounds, the TAAO-SDTIM model has offered superior PDR of 60.63% whereas the CHICD, FABC, and ABC methods have reached lower PDR of 56.05%, 50.07%, and 38.99% correspondingly.

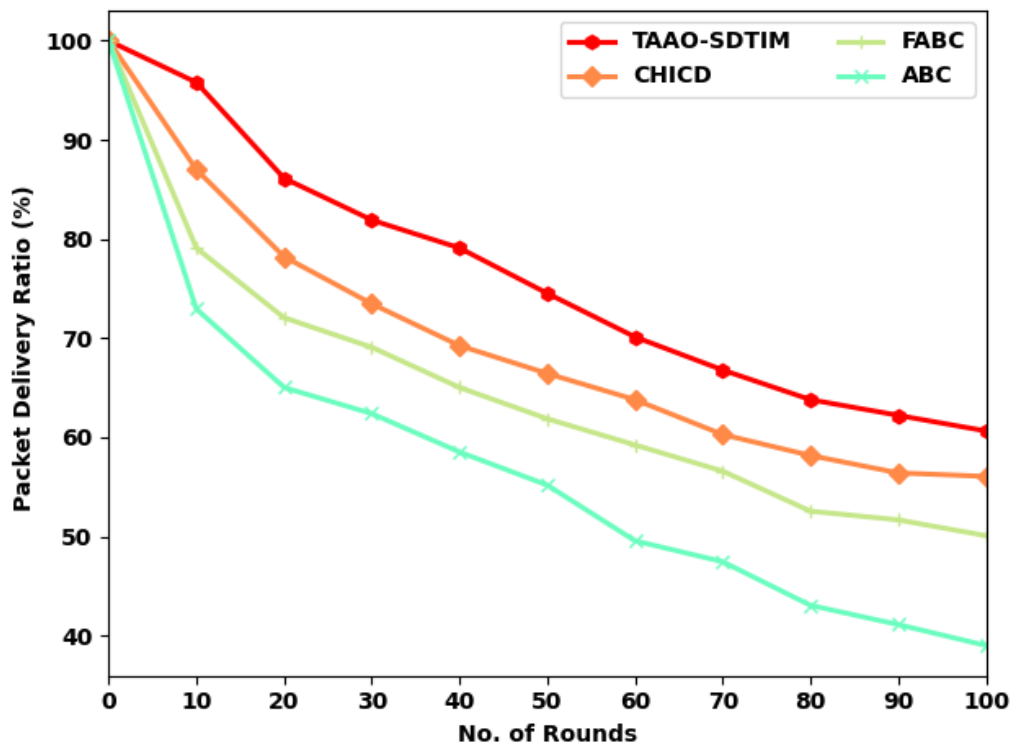


Fig. 3. PDR analysis of TAAO-SDTIM method on Blackhole Attack (50 Nodes)

Table 2 Throughput analysis of TAAO-SDTIM method with exiting methods on Blackhole Attack (50 Nodes)

Throughput (%)				
No. of Rounds	TAAO-SDTIM	CHICD	FABC	ABC
0	100.00	100.00	100.00	100.00
10	90.70	87.76	86.52	84.19
20	85.59	81.40	77.68	72.71
30	80.93	75.19	72.71	67.75
40	76.75	71.01	68.06	64.80
50	71.47	66.20	64.80	62.01
60	68.84	62.94	60.77	58.29
70	66.97	59.69	57.05	55.03
80	63.41	57.36	52.86	50.69

90	59.69	54.88	48.36	46.81
100	59.69	54.88	47.43	44.80

Table 2 and Fig. 4 examine the throughput (THPT) of the TAAO-SDTIM model with other models under blackhole attacks with 50 nodes. The experimental values indicated that the TAAO-SDTIM model has resulted in maximum THPT over the other methods. For sample, with 10 rounds, the TAAO-SDTIM model has accessible higher THPT of 90.70% whereas the CHICD, FABC, and ABC models have obtained lower THPT of 87.76%, 86.52%, and 84.19% respectively. Followed by, with 50 rounds, the TAAO-SDTIM technique has obtainable superior THPT of 71.47% whereas the CHICD, FABC, and ABC approaches have obtained minimal THPT of 66.20%, 64.80%, and 62.01% correspondingly. At last, with 100 rounds, the TAAO-SDTIM model has offered higher THPT of 59.69% whereas the CHICD, FABC, and ABC methodologies have reached minimum THPT of 54.88%, 47.43%, and 44.80% correspondingly.

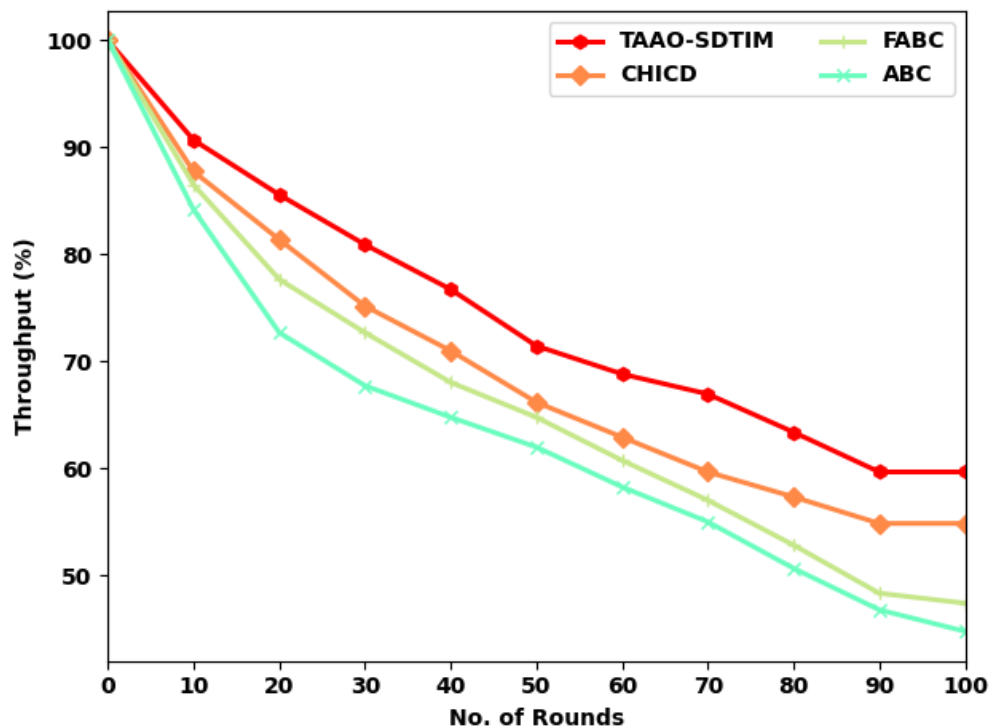


Fig. 4. Throughput analysis of TAAO-SDTIM method on Blackhole Attack (50 Nodes)

Table 3 Delay analysis of TAAO-SDTIM method with exiting methods on Blackhole Attack (50 Nodes)

No. of Rounds	Delay (ms)			
	TAAO-SDTIM	CHICD	FABC	ABC
0	0.00	0.00	0.00	0.00
10	165.95	178.68	208.80	244.11
20	183.22	226.45	263.84	292.92
30	195.30	239.95	277.34	320.96
40	195.30	248.26	283.57	340.69

50	195.30	256.57	290.84	351.07
60	198.41	256.57	289.80	352.11
70	198.41	256.57	288.76	350.03
80	195.30	262.80	291.88	345.88
90	196.33	265.91	291.88	342.76
100	193.22	267.99	289.80	332.38

A detailed delay (DEL) inspection of the TAAO-SDTIM model with existing models is made in Table 3 and Fig. 5. The experimental outcomes implied that the TAAO-SDTIM model has been able to effectual outcomes with minimal values of DEL. For instance, under 10 rounds, the TAAO-SDTIM model has exhibited lower DEL of 165.95ms whereas the CHICD, FABC, and ABC models have obtained higher DEL of 178.68ms, 208.80ms, and 244.11ms respectively. Also, under 50 rounds, the TAAO-SDTIM technique has exhibited lower DEL of 195.30ms whereas the CHICD, FABC, and ABC models have obtained superior DEL of 256.57ms, 290.84ms, and 351.07ms respectively. In addition, under 100 rounds, the TAAO-SDTIM approach has exhibited minimal DEL of 193.22ms whereas the CHICD, FABC, and ABC techniques have reached maximal DEL of 267.99ms, 289.80ms, and 332.38ms correspondingly.

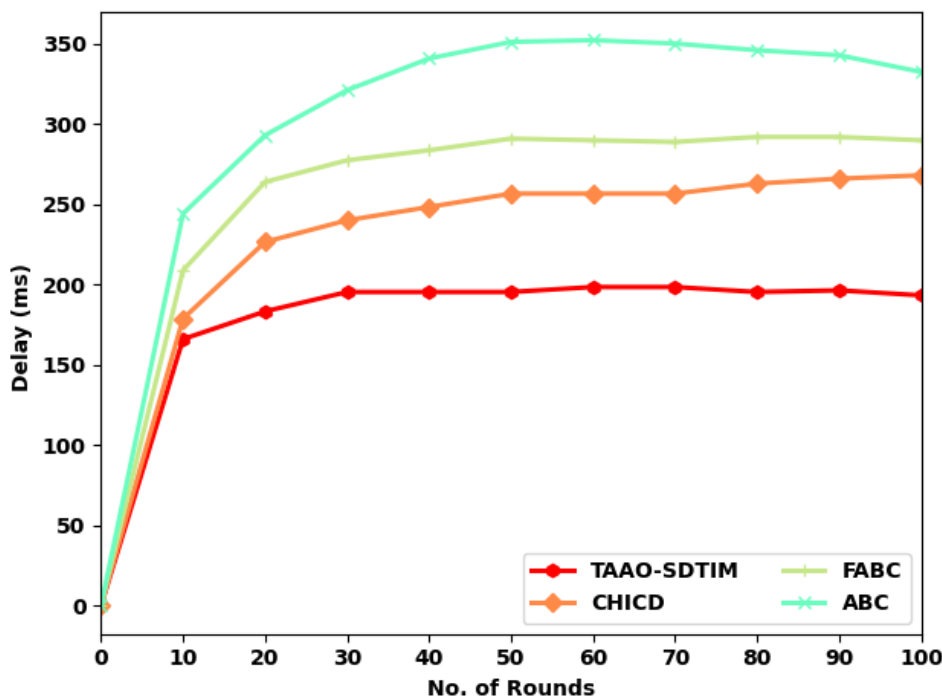


Fig. 5. Delay analysis of TAAO-SDTIM method on Blackhole Attack (50 Nodes)

Table 4 PDR analysis of TAAO-SDTIM method with exiting methods on Sinkhole attack (50 Nodes)

Packet Delivery Ratio (%)				
No. of Rounds	TAAO-SDTIM	CHICD	FABC	ABC
0	100.00	100.00	100.00	100.00
10	88.98	82.73	79.98	73.55

20	79.80	74.10	74.65	67.30
30	76.30	70.61	68.96	61.43
40	72.63	67.49	65.83	59.77
50	69.14	65.10	63.08	57.38
60	65.65	60.69	59.40	53.34
70	62.53	58.12	57.75	49.49
80	61.43	57.94	52.98	46.73
90	59.77	55.18	52.79	43.97
100	59.59	54.08	50.59	43.24

Table 4 and Fig. 6 examine the PDR of the TAAO-SDTIM model with other models under sinkhole attacks with 50 nodes. The experimental values indicated that the TAAO-SDTIM model has resulted in higher PDR over the other methodologies. For sample, with 10 rounds, the TAAO-SDTIM model has obtainable higher PDR of 88.98% whereas the CHICD, FABC, and ABC models have obtained minimal PDR of 82.73%, 79.98%, and 73.55% correspondingly. Besides, with 50 rounds, the TAAO-SDTIM model has offered superior PDR of 69.14% whereas the CHICD, FABC, and ABC models have obtained lower PDR of 65.10%, 63.08%, and 57.38% respectively. Followed by, with 100 rounds, the TAAO-SDTIM model has offered higher PDR of 59.59% whereas the CHICD, FABC, and ABC models have obtained lower PDR of 54.08%, 50.59%, and 43.24% correspondingly.

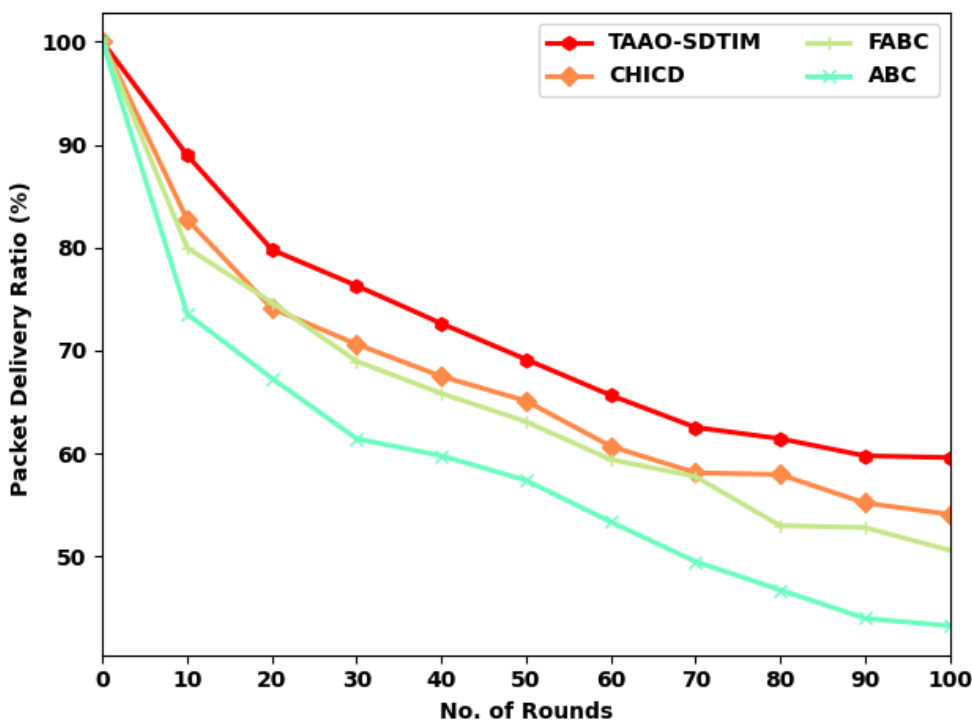


Fig. 6. PDR analysis of TAAO-SDTIM method on Sinkhole Attack (50 Nodes)

Table 5 Throughput analysis of TAAO-SDTIM method with exiting methods on Sinkhole attack (50 Nodes)

Throughput (%)				
No. of Rounds	TAAO-SDTIM	CHICD	FABC	ABC
0	100.00	100.00	100.00	100.00

10	90.66	87.08	80.09	74.03
20	85.37	81.64	76.36	70.76
30	80.55	77.60	74.49	67.96
40	76.36	71.54	72.47	65.63
50	72.16	67.96	70.29	64.23
60	67.81	63.61	66.56	62.37
70	65.48	61.12	60.50	59.57
80	63.45	59.41	58.01	57.55
90	61.59	58.17	56.46	55.06
100	60.66	57.08	55.37	53.51

Table 5 and Fig. 7 inspect the THPT of the TAAO-SDTIM technique with other models under sinkhole attacks with 50 nodes. The experimental values indicated that the TAAO-SDTIM model has resulted in maximum THPT over the other methods. For sample, with 10 rounds, the TAAO-SDTIM model has obtainable higher THPT of 90.66% whereas the CHICD, FABC, and ABC methods have obtained lower THPT of 87.08%, 80.09%, and 74.03% correspondingly. At the same time, with 50 rounds, the TAAO-SDTIM model has offered higher THPT of 72.16% whereas the CHICD, FABC, and ABC models have obtained lower THPT of 67.96%, 70.29%, and 64.23% respectively. Eventually, with 100 rounds, the TAAO-SDTIM model has offered higher THPT of 60.66% whereas the CHICD, FABC, and ABC models have obtained lower THPT of 57.08%, 55.37%, and 53.51% correspondingly.

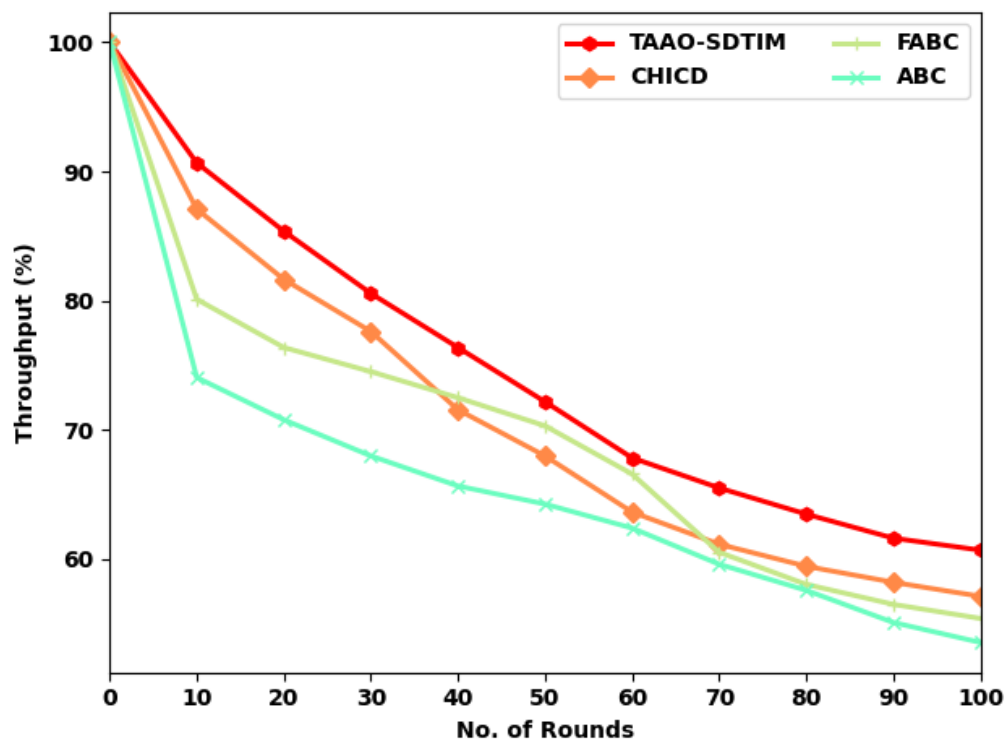


Fig. 7. Throughput analysis of TAAO-SDTIM method on Sinkhole Attack (50 Nodes)

Table 6 Delay analysis of TAAO-SDTIM method with exiting methods on Sinkhole attack (50 Nodes)

Delay (ms)
------------

No. of Rounds	TAAO-SDTIM	CHICD	FABC	ABC
0	0.00	0.00	0.00	0.00
10	135.86	156.55	179.94	206.03
20	159.25	191.64	209.63	230.32
30	162.85	206.93	224.02	253.71
40	162.85	215.03	232.12	261.81
50	164.65	217.73	236.62	265.41
60	163.75	216.83	241.12	267.21
70	163.75	216.83	242.92	272.61
80	162.85	215.93	242.92	276.20
90	167.34	215.93	243.82	275.30
100	161.95	210.53	243.82	275.30

A detailed DEL examination of the TAAO-SDTIM model with existing models is made in Table 6 and Fig. 8. The experimental outcomes implied that the TAAO-SDTIM model has been able to effectual outcomes with minimal values of DEL. For instance, under 10 rounds, the TAAO-SDTIM model has exhibited lower DEL of 135.86ms whereas the CHICD, FABC, and ABC models have obtained higher DEL of 156.55ms, 179.94ms, and 206.03ms correspondingly. Similarly, under 50 rounds, the TAAO-SDTIM approach has exhibited lower DEL of 164.65ms whereas the CHICD, FABC, and ABC methods have obtained higher DEL of 217.73ms, 236.62ms, and 265.41ms respectively. Finally, under 100 rounds, the TAAO-SDTIM model has exhibited lower DEL of 161.95ms whereas the CHICD, FABC, and ABC models have obtained higher DEL of 210.53ms, 243.82ms, and 275.30ms correspondingly.

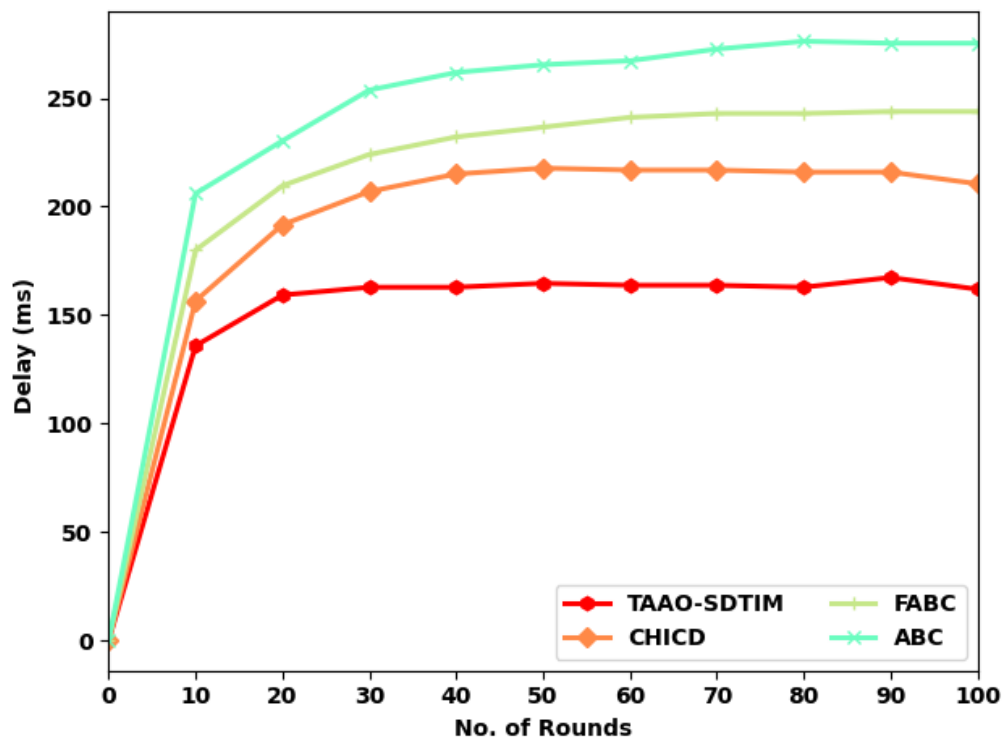


Fig. 8. Delay analysis of TAAO-SDTIM method on Sinkhole Attack (50 Nodes)

Afterwards investigative the above results and discussion, it can be ensured that the TAAO-SDTIM model has accomplished maximum performance over the other recent methods.

#### 4. Conclusion

In this study, a novel TAAO-SDTIM model is presented for achieving maximum security and information management in WSN. The presented TAAO-SDTIM technique determines optimal set of routes to BS utilizing a FF containing three parameters like RE, DBS, and TL. The incorporation of the trust level of the nodes in the route selection process aids in appropriately selecting highly secure nodes in the data transmission procedure. For ensuring the enhanced performance of the TAAO-SDTIM model, a wide range of experiments are executed and the results pointed out the improved outcomes of the TAAO-SDTIM model over the other recent approaches. Thus, the TAAO-SDTIM model can be appeared as an effective solution to achieve secure data transmission in WSN.

## References

- [1] Arjunan, S. and Sujatha, P., 2018. Lifetime maximization of wireless sensor network using fuzzy based unequal clustering and ACO based routing hybrid protocol. *Applied Intelligence*, 48(8), pp.2229-2246.
- [2] Fang, W., Zhang, W., Yang, W., Li, Z., Gao, W. and Yang, Y., 2021. Trust management-based and energy efficient hierarchical routing protocol in wireless sensor networks. *Digital Communications and Networks*, 7(4), pp.470-478.
- [3] Arjunan, S. and Pothula, S., 2019. A survey on unequal clustering protocols in wireless sensor networks. *Journal of King Saud University-Computer and Information Sciences*, 31(3), pp.304-317.
- [4] Khan, T. and Singh, K., 2021. TASRP: a trust aware secure routing protocol for wireless sensor networks. *International Journal of Innovative Computing and Applications*, 12(2-3), pp.108-122.
- [5] Arjunan, S., Pothula, S. and Ponnurangam, D., 2018. F5N-based unequal clustering protocol (F5NUCP) for wireless sensor networks. *International Journal of Communication Systems*, 31(17), p.e3811.
- [6] Uthayakumar, J., Vengattaraman, T. and Arjunan, S., 2022. An Efficient Near Lossless Image Compression Algorithm Using Dissemination of Spatial Correlation for Remote Sensing Color Images. *Wireless Personal Communications*, 122(4), pp.2963-2994.
- [7] Famila, S., Jawahar, A., Sariga, A. and Shankar, K., 2020. Improved artificial bee colony optimization based clustering algorithm for SMART sensor environments. *Peer-to-Peer Networking and Applications*, 13(4), pp.1071-1079.
- [8] Khan, T., Singh, K., Hasan, M.H., Ahmad, K., Reddy, G.T., Mohan, S. and Ahmadian, A., 2021. ETERS: A comprehensive energy aware trust-based efficient routing scheme for adversarial WSNs. *Future Generation Computer Systems*, 125, pp.921-943.
- [9] Hema Kumar, M., Mohanraj, V., Suresh, Y., Senthilkumar, J. and Nagalalli, G., 2021. Trust aware localized routing and class based dynamic block chain encryption scheme for improved security in WSN. *Journal of Ambient Intelligence and Humanized Computing*, 12(5), pp.5287-5295.
- [10] Sakthidasan, K., Gao, X.Z., Devabalaji, K.R. and Roopa, Y.M., 2021. Energy based random repeat trust computation approach and Reliable Fuzzy and Heuristic Ant Colony mechanism for improving QoS in WSN. *Energy Reports*, 7, pp.7967-7976.
- [11] Selvi, M., Santhosh Kumar, S.V.N., Ganapathy, S., Ayyanar, A., Khanna Nehemiah, H. and Kannan, A., 2021. An energy efficient clustered gravitational and fuzzy based routing algorithm in WSNs. *Wireless Personal Communications*, 116(1), pp.61-90.
- [12] Shafiq, M., Ashraf, H., Ullah, A., Masud, M., Azeem, M., Jhanjhi, N. and Humayun, M., 2021. Robust cluster-based routing protocol for IoT-assisted smart devices in WSN. *Comput. Mater. Contin.*, 67, pp.3505-3521.
- [13] Sharma, D. and Tomar, G.S., 2021. Energy Efficient Multitier Random DEC Routing Protocols for WSN: In Agricultural. *Wireless Personal Communications*, 120(1), pp.727-747.
- [14] Miao, Y., Zhao, C. and Wu, H., 2021. Non-uniform clustering routing protocol of wheat farmland based on effective energy consumption. *International Journal of Agricultural and Biological Engineering*, 14(3), pp.163-170.
- [15] Rathore, P.S., Chatterjee, J.M., Kumar, A. and Sujatha, R., 2021. Energy-efficient cluster head selection through relay approach for WSN. *The Journal of Supercomputing*, 77(7), pp.7649-7675.
- [16] Abualigah, L., Yousri, D., Abd Elaziz, M., Ewees, A.A., Al-Qaness, M.A. and Gandomi, A.H., 2021. Aquila optimizer: a novel meta-heuristic optimization algorithm. *Computers & Industrial Engineering*, 157, p.107250.

- [17] AlRassas, A.M., Al-qaness, M.A., Ewees, A.A., Ren, S., Abd Elaziz, M., Damaševičius, R. and Krilavičius, T., 2021. Optimized ANFIS model using Aquila Optimizer for oil production forecasting. *Processes*, 9(7), p.1194.
- [18] Rodrigues, P. and John, J., 2020. Joint trust: An approach for trust-aware routing in WSN. *Wireless Networks*, 26(5), pp.3553-3568.